Python For Data Science

python™ Basics Cheat Sheet

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> Variables and Data Types

Variable Assignment

```
>>> x=5
>>> x
 5
```

Calculations With Variables

```
>>> x+2 #Sum of two variables
 7
>>> x-2 #Subtraction of two variables
 3
>>> x*2 #Multiplication of two variables
 10
>>> x**2 #Exponentiation of a variable
 25
>>> x%2 #Remainder of a variable
 1
>>> x/float(2) #Division of a variable
 2.5
```

Types and Type Conversion

str()

```
'5', '3.45', 'True' #Variables to strings
```

int()

```
5, 3, 1 #Variables to integers
```

float()

```
5.0, 1.0 #Variables to floats
```

bool()

```
True, True, True #Variables to booleans
```

> Libraries

pandas — Data analysis
NumPy — Scientific computing
matplotlib — 2D plotting
learn — Machine learning

Import Libraries

```
>>> import numpy
>>> import numpy as np
```

Selective import

```
>>> from math import pi
```

> Strings

```
>>> my_string = 'thisStringIsAwesome'
>>> my_string
 'thisStringIsAwesome'
```

String Operations

```
>>> my_string * 2
 'thisStringIsAwesomethisStringIsAwesome'
>>> my_string + 'Innit'
 'thisStringIsAwesomeInnit'
>>> 'm' in my_string
 True
```

String Indexing

Index starts at 0

```
>>> my_string[3]
>>> my_string[4:9]
```

String Methods

```
>>> my_string.upper() #String to uppercase
>>> my_string.lower() #String to lowercase
>>> my_string.count('w') #Count String elements
>>> my_string.replace('e', 'i') #Replace String elements
>>> my_string.strip() #Strip whitespaces
```

> NumPy Arrays

Also see Lists

```
>>> my_list = [1, 2, 3, 4]
>>> my_array = np.array(my_list)
>>> my_2darray = np.array([[1,2,3],[4,5,6]])
```

Selecting Numpy Array Elements

Index starts at 0

Subset

```
>>> my_array[1] #Select item at index 1
 2
```

Slice

```
>>> my_array[0:2] #Select items at index 0 and 1
 array([1, 2])
```

Subset 2D Numpy arrays

```
>>> my_2darray[:,0] #my_2darray[rows, columns]
 array([1, 4])
```

Numpy Array Operations

```
>>> my_array > 3
 array([False, False, False, True], dtype=bool)
>>> my_array * 2
 array([2, 4, 6, 8])
>>> my_array + np.array([5, 6, 7, 8])
 array([6, 8, 10, 12])
```

Numpy Array Functions

```
>>> my_array.shape #Get the dimensions of the array
>>> np.append(other_array) #Append items to an array
>>> np.insert(my_array, 1, 5) #Insert items in an array
>>> np.delete(my_array,[1]) #Delete items in an array
>>> np.mean(my_array) #Mean of the array
>>> np.median(my_array) #Median of the array
>>> my_array.corrcoef() #Correlation coefficient
>>> np.std(my_array) #Standard deviation
```

> Lists

Also see NumPy Arrays

```
>>> a = 'is'
>>> b = 'nice'
>>> my_list = ['my', 'list', a, b]
>>> my_list2 = [[4,5,6,7], [3,4,5,6]]
```

Selecting List Elements

Index starts at 0

Subset

```
>>> my_list[1] #Select item at index 1
>>> my_list[-3] #Select 3rd last item
```

Slice

```
>>> my_list[1:3] #Select items at index 1 and 2
>>> my_list[1:] #Select items after index 0
>>> my_list[:3] #Select items before index 3
>>> my_list[:] #Copy my_list
```

Subset Lists of Lists

```
>>> my_list2[1][0] #my_list[list][itemOfList]
>>> my_list2[1][:2]
```

List Operations

```
>>> my_list + my_list
['my', 'list', 'is', 'nice', 'my', 'list', 'is', 'nice']
>>> my_list * 2
['my', 'list', 'is', 'nice', 'my', 'list', 'is', 'nice']
>>> my_list2 > 4
True
```

List Methods

```
>>> my_list.index(a) #Get the index of an item
>>> my_list.count(a) #Count an item
>>> my_list.append('!') #Append an item at a time
>>> my_list.remove('!') #Remove an item
>>> del(my_list[0:1]) #Remove an item
>>> my_list.reverse() #Reverse the list
>>> my_list.extend('!') #Append an item
>>> my_list.pop(-1) #Remove an item
>>> my_list.insert(0,'!') #Insert an item
>>> my_list.sort() #Sort the list
```

> Python IDEs (Integrated Development Environment)

ANACONDA. — Leading open data science platform powered by Python

SPYDER — Free IDE that is included with Anaconda

jupyter — Create and share documents with live code

> Asking For Help

```
>>> help(str)
```

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Python For Data Science
NumPy Cheat Sheet

Learn NumPy online at www.DataCamp.com

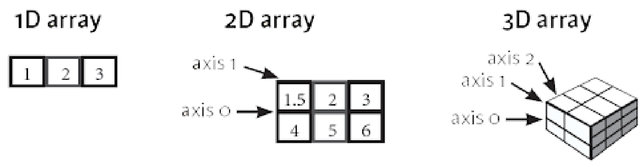
Numpy

The NumPy library is the core library for scientific computing in Python. It provides a high-performance multidimensional array object, and tools for working with these arrays

Use the following import convention:

```
>>> import numpy as np
```

NumPy Arrays



> Creating Arrays

```
>>> a = np.array([1,2,3])
>>> b = np.array([(1.5,2,3), (4,5,6)], dtype = float)
>>> c = np.array([[(1.5,2,3), (4,5,6)],[(3,2,1), (4,5,6)]], dtype = float)
```

Initial Placeholders

```
>>> np.zeros((3,4)) #Create an array of zeros
>>> np.ones((2,3,4),dtype=np.int16) #Create an array of ones
>>> d = np.arange(10,25,5) #Create an array of evenly spaced values (step value)
>>> np.linspace(0,2,9) #Create an array of evenly spaced values (number of samples)
>>> e = np.full((2,2),7) #Create a constant array
>>> f = np.eye(2) #Create a 2X2 identity matrix
>>> np.random.random((2,2)) #Create an array with random values
>>> np.empty((3,2)) #Create an empty array
```

> I/O

Saving & Loading On Disk

```
>>> np.save('my_array', a)
>>> np.savez('array.npz', a, b)
>>> np.load('my_array.npy')
```

Saving & Loading Text Files

```
>>> np.loadtxt("myfile.txt")
>>> np.genfromtxt("my_file.csv", delimiter=',')
>>> np.savetxt("myarray.txt", a, delimiter=" ")
```

> Asking For Help

```
>>> np.info(np.ndarray.dtype)
```

> Inspecting Your Array

```
>>> a.shape #Array dimensions
>>> len(a) #Length of array
>>> b.ndim #Number of array dimensions
>>> e.size #Number of array elements
>>> b.dtype #Data type of array elements
>>> b.dtype.name #Name of data type
>>> b.astype(int) #Convert an array to a different type
```

> Data Types

```
>>> np.int64 #Signed 64-bit integer types
>>> np.float32 #Standard double-precision floating point
>>> np.complex #Complex numbers represented by 128 floats
>>> np.bool #Boolean type storing TRUE and FALSE values
>>> np.object #Python object type
>>> np.string_ #Fixed-length string type
>>> np.unicode_ #Fixed-length unicode type
```

> Array Mathematics

Arithmetic Operations

```
>>> g = a - b #Subtraction
 array([[-0.5, 0. , 0. ],
        [-3. , -3. , -3. ]])
>>> np.subtract(a,b) #Subtraction
>>> b + a #Addition
 array([[ 2.5, 4. , 6. ],
        [ 5. , 7. , 9. ]])
>>> np.add(b,a) #Addition
>>> a / b #Division
 array([[ 0.66666667, 1. , 1. ],
        [ 0.25 , 0.4 , 0.5 ]])
>>> np.divide(a,b) #Division
>>> a * b #Multiplication
 array([[ 1.5, 4. , 9. ],
        [ 4. , 10. , 18. ]])
>>> np.multiply(a,b) #Multiplication
>>> np.exp(b) #Exponentiation
>>> np.sqrt(b) #Square root
>>> np.sin(a) #Print sines of an array
>>> np.cos(b) #Element-wise cosine
>>> np.log(a) #Element-wise natural logarithm
>>> e.dot(f) #Dot product
 array([[ 7., 7.],
        [ 7., 7.]])
```

Comparison

```
>>> a == b #Element-wise comparison
 array([[False, True, True],
        [False, False, False]], dtype=bool)
>>> a < 2 #Element-wise comparison
 array([True, False, False], dtype=bool)
>>> np.array_equal(a, b) #Array-wise comparison
```

Aggregate Functions

```
>>> a.sum() #Array-wise sum
>>> a.min() #Array-wise minimum value
>>> b.max(axis=0) #Maximum value of an array row
>>> b.cumsum(axis=1) #Cumulative sum of the elements
>>> a.mean() #Mean
>>> np.median(b) #Median
>>> np.corrcoef(a) #Correlation coefficient
>>> np.std(b) #Standard deviation
```

> Copying Arrays

```
>>> h = a.view() #Create a view of the array with the same data
>>> np.copy(a) #Create a copy of the array
>>> h = a.copy() #Create a deep copy of the array
```

> Sorting Arrays

```
>>> a.sort() #Sort an array
>>> c.sort(axis=0) #Sort the elements of an array's axis
```

> Subsetting, Slicing, Indexing

Subsetting

```
>>> a[2] #Select the element at the 2nd index
 3
>>> b[1,2] #Select the element at row 1 column 2 (equivalent to b[1][2])
 6.0
```

Slicing

```
>>> a[0:2] #Select items at index 0 and 1
 array([1, 2])
>>> b[0:2,1] #Select items at rows 0 and 1 in column 1
 array([ 2., 5.])
>>> b[:1] #Select all items at row 0 (equivalent to b[0:1, :])
 array([[1.5, 2., 3.]])
>>> c[1,...] #Same as [1,:,:]
 array([[[ 3., 2., 1.],
         [ 4., 5., 6.]]])
>>> a[ : :-1] #Reversed array a array([3, 2, 1])
```

Boolean Indexing

```
>>> a[a<2] #Select elements from a less than 2
 array([1])
```

Fancy Indexing

```
>>> b[[1, 0, 1, 0],[0, 1, 2, 0]] #Select elements (1,0),(0,1),(1,2) and (0,0)
 array([ 4. , 2. , 6. , 1.5])
>>> b[[1, 0, 1, 0]][:,[0,1,2,0]] #Select a subset of the matrix's rows and columns
 array([[ 4. ,5. , 6. , 4. ],
        [ 1.5, 2. , 3. , 1.5],
        [ 4. , 5. , 6. , 4. ],
        [ 1.5, 2. , 3. , 1.5]])
```

> Array Manipulation

Transposing Array

```
>>> i = np.transpose(b) #Permute array dimensions
>>> i.T #Permute array dimensions
```

Changing Array Shape

```
>>> b.ravel() #Flatten the array
>>> g.reshape(3,-2) #Reshape, but don't change data
```

Adding/Removing Elements

```
>>> h.resize((2,6)) #Return a new array with shape (2,6)
>>> np.append(h,g) #Append items to an array
>>> np.insert(a, 1, 5) #Insert items in an array
>>> np.delete(a,[1]) #Delete items from an array
```

Combining Arrays

```
>>> np.concatenate((a,d),axis=0) #Concatenate arrays
 array([ 1, 2, 3, 10, 15, 20])
>>> np.vstack((a,b)) #Stack arrays vertically (row-wise)
 array([[ 1. , 2. , 3. ],
        [ 1.5, 2. , 3. ],
        [ 4. , 5. , 6. ]])
>>> np.r_[e,f] #Stack arrays vertically (row-wise)
>>> np.hstack((e,f)) #Stack arrays horizontally (column-wise)
 array([[ 7., 7., 1., 0.],
        [ 7., 7., 0., 1.]])
>>> np.column_stack((a,d)) #Create stacked column-wise arrays
 array([[ 1, 10],
        [ 2, 15],
        [ 3, 20]])
>>> np.c_[a,d] #Create stacked column-wise arrays
```

Splitting Arrays

```
>>> np.hsplit(a,3) #Split the array horizontally at the 3rd index
 [array([1]),array([2]),array([3])]
>>> np.vsplit(c,2) #Split the array vertically at the 2nd index
 [array([[[ 1.5, 2. , 1. ],
          [ 4. , 5. , 6. ]]]),
 array([[[ 3., 2., 3.],
         [ 4., 5., 6.]]])]
```

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Python For Data Science

SciPy Cheat Sheet

Learn SciPy online at www.DataCamp.com

SciPy

The **SciPy** library is one of the core packages for scientific computing that provides mathematical algorithms and convenience functions built on the NumPy extension of Python.

> Interacting With NumPy

Also see NumPy

```
>>> import numpy as np
>>> a = np.array([1,2,3])
>>> b = np.array([(1+5j,2j,3j), (4j,5j,6j)])
>>> c = np.array([[(1.5,2,3), (4,5,6)], [(3,2,1), (4,5,6)]])
```

Index Tricks

```
>>> np.mgrid[0:5,0:5] #Create a dense meshgrid
>>> np.ogrid[0:2,0:2] #Create an open meshgrid
>>> np.r_[[3,[0]*5,-1:1:10j] #Stack arrays vertically (row-wise)
>>> np.c_[b,c] #Create stacked column-wise arrays
```

Shape Manipulation

```
>>> np.transpose(b) #Permute array dimensions
>>> b.flatten() #Flatten the array
>>> np.hstack((b,c)) #Stack arrays horizontally (column-wise)
>>> np.vstack((a,b)) #Stack arrays vertically (row-wise)
>>> np.hsplit(c,2) #Split the array horizontally at the 2nd index
>>> np.vpslit(d,2) #Split the array vertically at the 2nd index
```

Polynomials

```
>>> from numpy import poly1d
>>> p = poly1d([3,4,5]) #Create a polynomial object
```

Vectorizing Functions

```
>>> def myfunc(a): if a < 0:
        return a*2
        else:
        return a/2
>>> np.vectorize(myfunc) #Vectorize functions
```

Type Handling

```
>>> np.real(c) #Return the real part of the array elements
>>> np.imag(c) #Return the imaginary part of the array elements
>>> np.real_if_close(c,tol=1000) #Return a real array if complex parts close to 0
>>> np.cast['f'](np.pi) #Cast object to a data type
```

Other Useful Functions

```
>>> np.angle(b,deg=True) #Return the angle of the complex argument
>>> g = np.linspace(0,np.pi,num=5) #Create an array of evenly spaced values(number of samples)
>>> g [3:] += np.pi
>>> np.unwrap(g) #Unwrap
>>> np.logspace(0,10,3) #Create an array of evenly spaced values (log scale)
>>> np.select([c<4],[c*2]) #Return values from a list of arrays depending on conditions
>>> misc.factorial(a) #Factorial
>>> misc.comb(10,3,exact=True) #Combine N things taken at k time
>>> misc.central_diff_weights(3) #Weights for Np-point central derivative
>>> misc.derivative(myfunc,1.0) #Find the n-th derivative of a function at a point
```

> Linear Algebra

Also see NumPy

You'll use the `linalg` and `sparse` modules.
Note that `scipy.linalg` contains and expands on `numpy.linalg`.

```
>>> from scipy import linalg, sparse
```

Creating Matrices

```
>>> A = np.matrix(np.random.random((2,2)))
>>> B = np.asmatrix(b)
>>> C = np.mat(np.random.random((10,5)))
>>> D = np.mat([[3,4], [5,6]])
```

Basic Matrix Routines

Inverse

```
>>> A.I #Inverse
>>> linalg.inv(A) #Inverse
>>> A.T #Tranpose matrix
>>> A.H #Conjugate transposition
>>> np.trace(A) #Trace
```

Norm

```
>>> linalg.norm(A) #Frobenius norm
>>> linalg.norm(A,1) #L1 norm (max column sum)
>>> linalg.norm(A,np.inf) #L inf norm (max row sum)
```

Rank

```
>>> np.linalg.matrix_rank(C) #Matrix rank
```

Determinant

```
>>> linalg.det(A) #Determinant
```

Solving linear problems

```
>>> linalg.solve(A,b) #Solver for dense matrices
>>> E = np.mat(a).T #Solver for dense matrices
>>> linalg.lstsq(D,E) #Least-squares solution to linear matrix equation
```

Generalized inverse

```
>>> linalg.pinv(C) #Compute the pseudo-inverse of a matrix (least-squares solver)
>>> linalg.pinv2(C) #Compute the pseudo-inverse of a matrix  (SVD)
```

Creating Sparse Matrices

```
>>> F = np.eye(3, k=1) #Create a 2X2 identity matrix
>>> G = np.mat(np.identity(2)) #Create a 2x2 identity matrix
>>> C[C > 0.5] = 0
>>> H = sparse.csr_matrix(C) #Compressed Sparse Row matrix
>>> I = sparse.csc_matrix(D) #Compressed Sparse Column matrix
>>> J = sparse.dok_matrix(A) #Dictionary Of Keys matrix
>>> E.todense() #Sparse matrix to full matrix
>>> sparse.isspmatrix_csc(A) #Identify sparse matrix
```

Sparse Matrix Routines

Inverse

```
>>> sparse.linalg.inv(I) #Inverse
```

Norm

```
>>> sparse.linalg.norm(I) #Norm
```

Solving linear problems

```
>>> sparse.linalg.spsolve(H,I) #Solver for sparse matrices
```

Sparse Matrix Functions

```
>>> sparse.linalg.expm(I) #Sparse matrix exponential
```

Sparse Matrix Decompositions

```
>>> la, v = sparse.linalg.eigs(F,1) #Eigenvalues and eigenvectors
>>> sparse.linalg.svds(H, 2) #SVD
```

> Asking For Help

```
>>> help(scipy.linalg.diagsvd)
>>> np.info(np.matrix)
```

Matrix Functions

Addition

```
>>> np.add(A,D) #Addition
```

Subtraction

```
>>> np.subtract(A,D) #Subtraction
```

Division

```
>>> np.divide(A,D) #Division
```

Multiplication

```
>>> np.multiply(D,A) #Multiplication
>>> np.dot(A,D) #Dot product
>>> np.vdot(A,D) #Vector dot product
>>> np.inner(A,D) #Inner product
>>> np.outer(A,D) #Outer product
>>> np.tensordot(A,D) #Tensor dot product
>>> np.kron(A,D) #Kronecker product
```

Exponential Functions

```
>>> linalg.expm(A) #Matrix exponential
>>> linalg.expm2(A) #Matrix exponential (Taylor Series)
>>> linalg.expm3(D) #Matrix exponential (eigenvalue decomposition)
```

Logarithm Function

```
>>> linalg.logm(A) #Matrix logarithm
```

Trigonometric Functions

```
>>> linalg.sinm(D) Matrix sine
>>> linalg.cosm(D) Matrix cosine
>>> linalg.tanm(A) Matrix tangent
```

Hyperbolic Trigonometric Functions

```
>>> linalg.sinhm(D) #Hypberbolic matrix sine
>>> linalg.coshm(D) #Hyperbolic matrix cosine
>>> linalg.tanhm(A) #Hyperbolic matrix tangent
```

Matrix Sign Function

```
>>> np.sigm(A) #Matrix sign function
```

Matrix Square Root

```
>>> linalg.sqrtm(A) #Matrix square root
```

Arbitrary Functions

```
>>> linalg.funm(A, lambda x: x*x) #Evaluate matrix function
```

Decompositions

Eigenvalues and Eigenvectors

```
>>> la, v = linalg.eig(A) #Solve ordinary or generalized eigenvalue problem for square matrix
>>> l1, l2 = la #Unpack eigenvalues
>>> v[:,0] #First eigenvector
>>> v[:,1] #Second eigenvector
>>> linalg.eigvals(A) #Unpack eigenvalues
```

Singular Value Decomposition

```
>>> U,s,Vh = linalg.svd(B) #Singular Value Decomposition (SVD)
>>> M,N = B.shape
>>> Sig = linalg.diagsvd(s,M,N) #Construct sigma matrix in SVD
```

LU Decomposition

```
>>> P,L,U = linalg.lu(C) #LU Decomposition
```

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Python For Data Science
Importing Data Cheat Sheet

Learn Python online at www.DataCamp.com

> Importing Data in Python

Most of the time, you'll use either NumPy or pandas to import your data:

```
>>> import numpy as np
>>> import pandas as pd
```

> Help

```
>>> np.info(np.ndarray.dtype)
>>> help(pd.read_csv)
```

> Text Files

Plain Text Files

```
>>> filename = 'huck_finn.txt'
>>> file = open(filename, mode='r') #Open the file for reading
>>> text = file.read() #Read a file's contents
>>> print(file.closed) #Check whether file is closed
>>> file.close() #Close file
>>> print(text)
```

Using the context manager with

```
>>> with open('huck_finn.txt', 'r') as file:
        print(file.readline()) #Read a single line
        print(file.readline())
        print(file.readline())
```

Table Data: Flat Files

Importing Flat Files with NumPy

```
>>> filename = 'huck_finn.txt'
>>> file = open(filename, mode='r') #Open the file for reading
>>> text = file.read() #Read a file's contents
>>> print(file.closed) #Check whether file is closed
>>> file.close() #Close file
>>> print(text)
```

Files with one data type

```
>>> filename = 'mnist.txt'
>>> data = np.loadtxt(filename,
                      delimiter=',', #String used to separate values
                      skiprows=2, #Skip the first 2 lines
                      usecols=[0,2], #Read the 1st and 3rd column
                      dtype=str) #The type of the resulting array
```

Files with mixed data type

```
>>> filename = 'titanic.csv'
>>> data = np.genfromtxt(filename,
                         delimiter=',',
                         names=True, #Look for column header
                         dtype=None)
>>> data_array = np.recfromcsv(filename)
#The default dtype of the np.recfromcsv() function is None
```

Importing Flat Files with Pandas

```
>>> filename = 'winequality-red.csv'
>>> data = pd.read_csv(filename,
                       nrows=5, #Number of rows of file to read
                       header=None, #Row number to use as col names
                       sep='\t', #Delimiter to use
                       comment='#', #Character to split comments
                       na_values=[""]) #String to recognize as NA/NaN
```

> Exploring Your Data

NumPy Arrays

```
>>> data_array.dtype #Data type of array elements
>>> data_array.shape #Array dimensions
>>> len(data_array) #Length of array
```

Pandas DataFrames

```
>>> df.head() #Return first DataFrame rows
>>> df.tail() #Return last DataFrame rows
>>> df.index #Describe index
>>> df.columns #Describe DataFrame columns
>>> df.info() #Info on DataFrame
>>> data_array = data.values #Convert a DataFrame to an a NumPy array
```

> SAS File

```
>>> from sas7bdat import SAS7BDAT
>>> with SAS7BDAT('urbanpop.sas7bdat') as file:
        df_sas = file.to_data_frame()
```

> Stata File

```
>>> data = pd.read_stata('urbanpop.dta')
```

> Excel Spreadsheets

```
>>> file = 'urbanpop.xlsx'
>>> data = pd.ExcelFile(file)
>>> df_sheet2 = data.parse('1960-1966',
                           skiprows=[0],
                           names=['Country',
                           'AAM: War(2002)'])
>>> df_sheet1 = data.parse(0,
                           parse_cols=[0],
                           skiprows=[0],
                           names=['Country'])
```

To access the sheet names, use the `sheet_names` **attribute:**

```
>>> data.sheet_names
```

> Relational Databases

```
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite://Northwind.sqlite')
```

Use the `table_names()` **method to fetch a list of table names:**

```
>>> table_names = engine.table_names()
```

Querying Relational Databases

```
>>> con = engine.connect()
>>> rs = con.execute("SELECT * FROM Orders")
>>> df = pd.DataFrame(rs.fetchall())
>>> df.columns = rs.keys()
>>> con.close()
```

Using the context manager with

```
>>> with engine.connect() as con:
        rs = con.execute("SELECT OrderID FROM Orders")
        df = pd.DataFrame(rs.fetchmany(size=5))
        df.columns = rs.keys()
```

Querying relational databases with pandas

```
>>> df = pd.read_sql_query("SELECT * FROM Orders", engine)
```

> Pickled Files

```
>>> import pickle
>>> with open('pickled_fruit.pkl', 'rb') as file:
        pickled_data = pickle.load(file)
```

> Matlab Files

```
>>> import scipy.io
>>> filename = 'workspace.mat'
>>> mat = scipy.io.loadmat(filename)
```

> HDF5 Files

```
>>> import h5py
>>> filename = 'H-H1_LOSC_4_v1-815411200-4096.hdf5'
>>> data = h5py.File(filename, 'r')
```

> Exploring Dictionaries

Querying relational databases with pandas

```
>>> print(mat.keys()) #Print dictionary keys
>>> for key in data.keys(): #Print dictionary keys
        print(key)
meta
quality
strain
>>> pickled_data.values() #Return dictionary values
>>> print(mat.items()) #Returns items in list format of (key, value) tuple pairs
```

Accessing Data Items with Keys

```
>>> for key in data ['meta'].keys() #Explore the HDF5
structure
        print(key)
Description
DescriptionURL
Detector
Duration
GPSstart
Observatory
Type
UTCstart
#Retrieve the value for a key
>>> print(data['meta']['Description'].value)
```

> Navigating Your FileSystem

Magic Commands

```
!ls  #List directory contents of files and directories
%cd .. #Change current working directory
%pwd #Return the current working directory path
```

OS Library

```
>>> import os
>>> path = "/usr/tmp"
>>> wd = os.getcwd() #Store the name of current directory in a string
>>> os.listdir(wd) #Output contents of the directory in a list
>>> os.chdir(path) #Change current working directory
>>> os.rename("test1.txt", #Rename a file
              "test2.txt")
>>> os.remove("test1.txt") #Delete an existing file
>>> os.mkdir("newdir") #Create a new directory
```

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Python For Data Science

Pandas Basics Cheat Sheet

Learn Pandas Basics online at www.DataCamp.com

Pandas

The **Pandas** library is built on NumPy and provides easy-to-use **data structures** and **data analysis** tools for the Python programming language.

Use the following import convention:

```
>>> import pandas as pd
```

> Pandas Data Structures

Series

A **one-dimensional** labeled array capable of holding any data type

Index →

a	3
b	-5
c	7
d	4

```
>>> s = pd.Series([3, -5, 7, 4], index=['a', 'b', 'c', 'd'])
```

Dataframe

A **two-dimensional** labeled data structure with columns of potentially different types

Columns →

Index →	Country	Capital	Population
0	Belgium	Brussels	11190846
1	India	New Delhi	1303171035
2	Brazil	Brasilia	207847528

```
>>> data = {'Country': ['Belgium', 'India', 'Brazil'],
            'Capital': ['Brussels', 'New Delhi', 'Brasília'],
            'Population': [11190846, 1303171035, 207847528]}
>>> df = pd.DataFrame(data,
                      columns=['Country', 'Capital', 'Population'])
```

> Dropping

```
>>> s.drop(['a', 'c']) #Drop values from rows (axis=0)
>>> df.drop('Country', axis=1) #Drop values from columns(axis=1)
```

> Asking For Help

```
>>> help(pd.Series.loc)
```

> Sort & Rank

```
>>> df.sort_index() #Sort by labels along an axis
>>> df.sort_values(by='Country') #Sort by the values along an axis
>>> df.rank() #Assign ranks to entries
```

> I/O

Read and Write to CSV

```
>>> pd.read_csv('file.csv', header=None, nrows=5)
>>> df.to_csv('myDataFrame.csv')
```

Read and Write to Excel

```
>>> pd.read_excel('file.xlsx')
>>> df.to_excel('dir/myDataFrame.xlsx', sheet_name='Sheet1')
```

Read multiple sheets from the same file

```
>>> xlsx = pd.ExcelFile('file.xls')
>>> df = pd.read_excel(xlsx, 'Sheet1')
```

Read and Write to SQL Query or Database Table

```
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite:///:memory:')
>>> pd.read_sql("SELECT * FROM my_table;", engine)
>>> pd.read_sql_table('my_table', engine)
>>> pd.read_sql_query("SELECT * FROM my_table;", engine)
```

read_sql() **is a convenience wrapper around** read_sql_table() **and** read_sql_query()

```
>>> df.to_sql('myDf', engine)
```

> Selection

Also see NumPy Arrays

Getting

```
>>> s['b'] #Get one element
 -5
>>> df[1:] #Get subset of a DataFrame
   Country Capital Population
 1 India New Delhi 1303171035
 2 Brazil Brasília 207847528
```

Selecting, Boolean Indexing & Setting

By Position

```
>>> df.iloc[[0],[0]] #Select single value by row & column
 'Belgium'
>>> df.iat([0],[0])
 'Belgium'
```

By Label

```
>>> df.loc[[0], ['Country']] #Select single value by row & column labels
 'Belgium'
>>> df.at([0], ['Country'])
 'Belgium'
```

By Label/Position

```
>>> df.ix[2] #Select single row of subset of rows
 Country Brazil
 Capital Brasília
 Population 207847528
>>> df.ix[:,'Capital'] #Select a single column of subset of columns
 0 Brussels
 1 New Delhi
 2 Brasília
>>> df.ix[1,'Capital'] #Select rows and columns
 'New Delhi'
```

Boolean Indexing

```
>>> s[~(s > 1)] #Series s where value is not >1
>>> s[(s < -1) | (s > 2)] #s where value is <-1 or >2
>>> df[df['Population']>1200000000] #Use filter to adjust DataFrame
```

Setting

```
>>> s['a'] = 6 #Set index a of Series s to 6
```

> Retrieving Series/DataFrame Information

Basic Information

```
>>> df.shape #(rows,columns)
>>> df.index #Describe index
>>> df.columns #Describe DataFrame columns
>>> df.info() #Info on DataFrame
>>> df.count() #Number of non-NA values
```

Summary

```
>>> df.sum() #Sum of values
>>> df.cumsum() #Cummulative sum of values
>>> df.min()/df.max() #Minimum/maximum values
>>> df.idxmin()/df.idxmax() #Minimum/Maximum index value
>>> df.describe() #Summary statistics
>>> df.mean() #Mean of values
>>> df.median() #Median of values
```

> Applying Functions

```
>>> f = lambda x: x*2
>>> df.apply(f) #Apply function
>>> df.applymap(f) #Apply function element-wise
```

> Data Alignment

Internal Data Alignment

NA values are introduced in the indices that don't overlap:

```
>>> s3 = pd.Series([7, -2, 3], index=['a', 'c', 'd'])
>>> s + s3
 a 10.0
 b NaN
 c 5.0
 d 7.0
```

Arithmetic Operations with Fill Methods

You can also do the internal data alignment yourself with the help of the fill methods:

```
>>> s.add(s3, fill_values=0)
 a 10.0
 b -5.0
 c 5.0
 d 7.0
>>> s.sub(s3, fill_value=2)
>>> s.div(s3, fill_value=4)
>>> s.mul(s3, fill_value=3)
```

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Python For Data Science

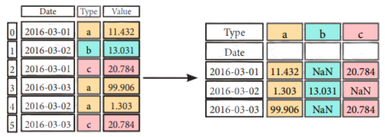
Data Wrangling in Pandas Cheat Sheet

Learn Data Wrangling online at www.DataCamp.com

> Reshaping Data

Pivot

```
>>> df3= df2.pivot(index='Date', #Spread rows into columns
                   columns='Type',
                   values='Value')
```

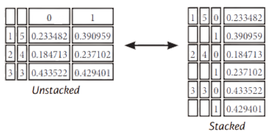


Pivot Table

```
>>> df4 = pd.pivot_table(df2, #Spread rows into
                         columns values='Value',
                         index='Date',
                         columns='Type'])
```

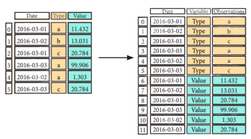
Stack / Unstack

```
>>> stacked = df5.stack() #Pivot a level of column labels
>>> stacked.unstack() #Pivot a level of index labels
```



Melt

```
>>> pd.melt(df2, #Gather columns into rows
            id_vars=["Date"],
            value_vars=["Type", "Value"],
            value_name="Observations")
```



> Iteration

```
>>> df.iteritems() #(Column-index, Series) pairs
>>> df.iterrows() #(Row-index, Series) pairs
```

> Missing Data

```
>>> df.dropna() #Drop NaN values
>>> df3.fillna(df3.mean()) #Fill NaN values with a predetermined value
>>> df2.replace("a", "f") #Replace values with others
```

> Advanced Indexing

Also see NumPy Arrays

Selecting

```
>>> df3.loc[:,(df3>1).any()] #Select cols with any vals >1
>>> df3.loc[:,(df3>1).all()] #Select cols with vals > 1
>>> df3.loc[:,df3.isnull().any()] #Select cols with NaN
>>> df3.loc[:,df3.notnull().all()] #Select cols without NaN
```

Indexing With `isin()`

```
>>> df[(df.Country.isin(df2.Type))] #Find same elements
>>> df3.filter(items="a","b"]) #Filter on values
>>> df.select(lambda x: not x%5) #Select specific elements
```

Where

```
>>> s.where(s > 0) #Subset the data
```

Query

```
>>> df6.query('second > first') #Query DataFrame
```

Setting/Resetting Index

```
>>> df.set_index('Country') #Set the index
>>> df4 = df.reset_index() #Reset the index
>>> df = df.rename(index=str, #Rename
                   DataFrame columns={"Country":"cntry",
                                      "Capital":"cptl",
                                      "Population":"ppltn"})
```

Reindexing

```
>>> s2 = s.reindex(['a','c','d','e','b'])
```

Forward Filling

```
>>> df.reindex(range(4),
               method='ffill')
```

```
   Country    Capital      Population
0 Belgium    Brussels     11190846
1 India      New Delhi    1303171035
2 Brazil     Brasília     207847528
3 Brazil     Brasília     207847528
```

Backward Filling

```
>>> s3 = s.reindex(range(5),
                   method='bfill')
```

```
0    3
1    3
2    3
3    3
4    3
```

MultiIndexing

```
>>> arrays = [np.array([1,2,3]),
              np.array([5,4,3])]
>>> df5 = pd.DataFrame(np.random.rand(3, 2), index=arrays)
>>> tuples = list(zip(*arrays))
>>> index = pd.MultiIndex.from_tuples(tuples,
                                      names=['first', 'second'])
>>> df6 = pd.DataFrame(np.random.rand(3, 2), index=index)
>>> df2.set_index(["Date", "Type"])
```

> Duplicate Data

```
>>> s3.unique() #Return unique values
>>> df2.duplicated('Type') #Check duplicates
>>> df2.drop_duplicates('Type', keep='last') #Drop duplicates
>>> df.index.duplicated() #Check index duplicates
```

> Grouping Data

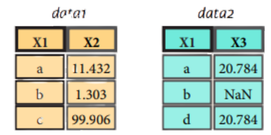
Aggregation

```
>>> df2.groupby(by=['Date','Type']).mean()
>>> df4.groupby(level=0).sum()
>>> df4.groupby(level=0).agg({'a':lambda x:sum(x)/len(x), 'b': np.sum})
```

Transformation

```
>>> customSum = lambda x: (x+x%2)
>>> df4.groupby(level=0).transform(customSum)
```

> Combining Data



Merge

```
>>> pd.merge(data1,
             data2,
             how='left',
             on='X1')
```

X1	X2	X3
a	11.432	20.784
b	1.303	NaN
c	99.906	NaN

```
>>> pd.merge(data1,
             data2,
             how='right',
             on='X1')
```

X1	X2	X3
a	11.432	20.784
b	1.303	NaN
d	NaN	20.784

```
>>> pd.merge(data1,
             data2,
             how='inner',
             on='X1')
```

X1	X2	X3
a	11.432	20.784
b	1.303	NaN

```
>>> pd.merge(data1,
             data2,
             how='outer',
             on='X1')
```

X1	X2	X3
a	11.432	20.784
b	1.303	NaN
c	99.906	NaN
d	NaN	20.784

Join

```
>>> data1.join(data2, how='right')
```

Concatenate

Vertical

```
>>> s.append(s2)
```

Horizontal/Vertical

```
>>> pd.concat([s,s2],axis=1, keys=['One','Two'])
>>> pd.concat([data1, data2], axis=1, join='inner')
```

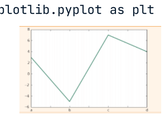
> Dates

```
>>> df2['Date']= pd.to_datetime(df2['Date'])
>>> df2['Date']= pd.date_range('2000-1-1',
                               periods=6,
                               freq='M')
>>> dates = [datetime(2012,5,1), datetime(2012,5,2)]
>>> index = pd.DatetimeIndex(dates)
>>> index = pd.date_range(datetime(2012,2,1), end, freq='BM')
```

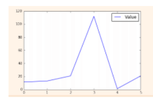
> Visualization

Also see Matplotlib

```
>>> import matplotlib.pyplot as plt
>>> s.plot()
>>> plt.show()
```



```
>>> df2.plot()
>>> plt.show()
```



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The Data Visualization Cheat Sheet

Learn Data Visualization online at www.DataCamp.com

How to use this cheat sheet

Use this cheat sheet for inspiration when making your next data visualizations. For more data visualization cheat sheets, check out our cheat sheets repository here.

> Part-to-whole charts

Pie chart

One of the most common ways to show part to whole data. It is also commonly used with percentages

USE CASES

1. Voting preference by age group
2. Market share of cloud providers

Donut pie chart

The donut pie chart is a variant of the pie chart, the difference being it has a hole in the center for readability

USE CASES

1. Android OS market share
2. Monthly sales by channel

Heat maps

Heatmaps are two-dimensional charts that use color shading to represent data trends.

USE CASES

1. Average monthly temperatures across the year
2. Departments with the highest amount of attrition over time

Stacked column chart

Best to compare subcategories within categorical data. Can also be used to compare percentages

USE CASES

1. Quarterly sales per region
2. Total car sales by producer

Treemap charts

2D rectangles whose size is proportional to the value being measured and can be used to display hierarchically structured data

USE CASES

1. Grocery sales count with categories
2. Stock price comparison by industry and company

> Capture a trend

Line chart

The most straightforward way to capture how a numeric variable is changing over time

USE CASES

1. Revenue in $ over time
2. Energy consumption in kWh over time
3. Google searches over time

Multi-line chart

Captures multiple numeric variables over time. It can include multiple axes allowing comparison of different units and scale ranges

USE CASES

1. Apple vs Amazon stocks over time
2. Lebron vs Steph Curry searches over time
3. Bitcoin vs Ethereum price over time

Area chart

Shows how a numeric value progresses by shading the area between line and the x-axis

USE CASES

1. Total sales over time
2. Active users over time

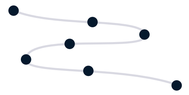
Stacked area chart

Most commonly used variation of area charts, the best use is to track the breakdown of a numeric value by subgroups

USE CASES

1. Active users over time by segment
2. Total revenue over time by country

Spline chart



Smoothened version of a line chart. It differs in that data points are connected with smoothed curves to account for missing values, as opposed to straight lines

USE CASES

1. Electricity consumption over time
2. CO2 emissions over time

> Visualize a single value

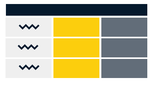
Card

Cards are great for showing and tracking KPIs in dashboards or presentations

USE CASES

1. Revenue to date on a sales dashboard
2. Total sign-ups after a promotion

Table chart



Best to be used on small datasets, it displays tabular data in a table

USE CASES

1. Account executive leaderboards
2. Registrations per webinar

Gauge chart

This chart is often used in executive dashboard reports to show relevant KPIs

USE CASES

1. NPS scores
2. Revenue to target

> Capture distributions

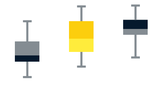
Histogram

Shows the distribution of a variable. It converts numerical data into bins as columns. The x-axis shows the range, and the y-axis represents the frequency

USE CASES

1. Distribution of salaries in an organization
2. Distribution of height in one cohort

Box plot



Shows the distribution of a variable using 5 key summary statistics—minimum, first quartile, median, third quartile, and maximum

USE CASES

1. Gas efficiency of vehicles
2. Time spent reading across readers

Violin plot

A variation of the box plot. It also shows the full distribution of the data alongside summary statistics

USE CASES

1. Time spent in restaurants across age groups
2. Length of pill effects by dose

Density plot

Visualizes a distribution by using smoothing to allow smoother distributions and better capture the distribution shape of the data

USE CASES

1. Distribution of price of hotel listings
2. Comparing NPS scores by customer segment

> Visualize relationships

Bar chart

One of the easiest charts to read which helps in quick comparison of categorical data. One axis contains categories and the other axis represents values

USE CASES

1. Volume of google searches by region
2. Market share in revenue by product

Column chart

Also known as a vertical bar chart, where the categories are placed on the x-axis. These are preferred over bar charts for short labels, date ranges, or negatives in values

USE CASES

1. Brand market share
2. Profit Analysis by region

Scatter plot

Most commonly used chart when observing the relationship between two variables. It is especially useful for quickly surfacing potential correlations between data points

USE CASES

1. Display the relationship between time-on-platform and churn
2. Display the relationship between salary and years spent at company

Connected scatterplot

A hybrid between a scatter plot and a line plot, the scatter dots are connected with a line

USE CASES

1. Cryptocurrency price index
2. Visualizing timelines and events when analyzing two variables

Bubble chart

Often used to visualize data points with 3 dimensions, namely visualized on the x-axis, y-axis, and with the size of the bubble. It tries to show relations between data points using location and size

USE CASES

1. Adwords analysis: CPC vs Conversions vs Share of total conversions
2. Relationship between life expectancy, GDP per capita, & population size

Word cloud chart

A convenient visualization for visualizing the most prevalent words that appear in a text

USE CASES

1. Top 100 used words by customers in customer service tickets

> Visualize a flow

Sankey chart

Useful for representing flows in systems. This flow can be any measurable quantity

USE CASES

1. Energy flow between countries
2. Supply chain volumes between warehouses

Chord chart

Useful for presenting weighted relationships or flows between nodes. Especially useful for highlighting the dominant or important flows

USE CASES

1. Export between countries to showcase biggest export partners
2. Supply chain volumes between the largest warehouses

Network chart

Similar to a graph, it consists of nodes and interconnected edges. It illustrates how different items have relationships with each other

USE CASES

1. How different airports are connected worldwide
2. Social media friend group analysis

Python For Data Science
Matplotlib Cheat Sheet

Learn Matplotlib online at www.DataCamp.com

Matplotlib

Matplotlib is a Python 2D plotting library which produces publication-quality figures in a variety of hardcopy formats and interactive environments across platforms.

> Prepare The Data

1D Data

```
>>> import numpy as np
>>> x = np.linspace(0, 10, 100)
>>> y = np.cos(x)
>>> z = np.sin(x)
```

2D Data or Images

```
>>> data = 2 * np.random.random((10, 10))
>>> data2 = 3 * np.random.random((10, 10))
>>> Y, X = np.mgrid[-3:3:100j, -3:3:100j]
>>> U = -1 - X**2 + Y
>>> V = 1 + X - Y**2
>>> from matplotlib.cbook import get_sample_data
>>> img = np.load(get_sample_data('axes_grid/bivariate_normal.npy'))
```

> Create Plot

```
>>> import matplotlib.pyplot as plt
```

Figure

```
>>> fig = plt.figure()
>>> fig2 = plt.figure(figsize=plt.figaspect(2.0))
```

Axes

All plotting is done with respect to an Axes. In most cases, a subplot will fit your needs.
A subplot is an axes on a grid system.

```
>>> fig.add_axes()
>>> ax1 = fig.add_subplot(221) #row-col-num
>>> ax3 = fig.add_subplot(212)
>>> fig3, axes = plt.subplots(nrows=2,ncols=2)
>>> fig4, axes2 = plt.subplots(ncols=3)
```

> Save Plot

```
>>> plt.savefig('foo.png')  #Save figures
>>> plt.savefig('foo.png', transparent=True)  #Save transparent figures
```

> Show Plot

```
>>> plt.show()
```

> Plotting Routines

1D Data

```
>>> fig, ax = plt.subplots()
>>> lines = ax.plot(x,y) #Draw points with lines or markers connecting them
>>> ax.scatter(x,y) #Draw unconnected points, scaled or colored
>>> axes[0,0].bar([1,2,3],[3,4,5]) #Plot vertical rectangles (constant width)
>>> axes[1,0].barh([0.5,1,2.5],[0,1,2]) #Plot horiontal rectangles (constant height)
>>> axes[1,1].axhline(0.45) #Draw a horizontal line across axes
>>> axes[0,1].axvline(0.65) #Draw a vertical line across axes
>>> ax.fill(x,y,color='blue') #Draw filled polygons
>>> ax.fill_between(x,y,color='yellow') #Fill between y-values and 0
```

2D Data

```
>>> fig, ax = plt.subplots()
>>> im = ax.imshow(img, #Colormapped or RGB arrays
                   cmap='gist_earth',
                   interpolation='nearest',
                   vmin=-2,
                   vmax=2)
>>> axes2[0].pcolor(data2) #Pseudocolor plot of 2D array
>>> axes2[0].pcolormesh(data) #Pseudocolor plot of 2D array
>>> CS = plt.contour(Y,X,U) #Plot contours
>>> axes2[2].contourf(data1) #Plot filled contours
>>> axes2[2]= ax.clabel(CS) #Label a contour plot
```

Vector Fields

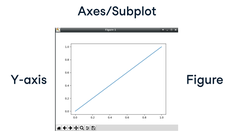
```
>>> axes[0,1].arrow(0,0,0.5,0.5) #Add an arrow to the axes
>>> axes[1,1].quiver(y,z) #Plot a 2D field of arrows
>>> axes[0,1].streamplot(X,Y,U,V) #Plot a 2D field of arrows
```

Data Distributions

```
>>> ax1.hist(y) #Plot a histogram
>>> ax3.boxplot(y) #Make a box and whisker plot
>>> ax3.violinplot(z) #Make a violin plot
```

> Plot Anatomy & Workflow

Plot Anatomy



Workflow

The basic steps to creating plots with matplotlib are:

1 Prepare Data 2 Create Plot 3 Plot 4 Customized Plot 5 Save Plot 6 Show Plot

```
>>> import matplotlib.pyplot as plt
>>> x = [1,2,3,4] #Step 1
>>> y = [10,20,25,30]
>>> fig = plt.figure() #Step 2
>>> ax = fig.add_subplot(111) #Step 3
>>> ax.plot(x, y, color='lightblue', linewidth=3) #Step 3, 4
>>> ax.scatter([2,4,6],
               [5,15,25],
               color='darkgreen',
               marker='^')
>>> ax.set_xlim(1, 6.5)
>>> plt.savefig('foo.png') #Step 5
>>> plt.show() #Step 6
```

> Close and Clear

```
>>> plt.cla() #Clear an axis
>>> plt.clf() #Clear the entire figure
>>> plt.close() #Close a window
```

> Plotting Cutomize Plot

Colors, Color Bars & Color Maps

```
>>> plt.plot(x, x, x, x**2, x, x**3)
>>> ax.plot(x, y, alpha = 0.4)
>>> ax.plot(x, y, c='k')
>>> fig.colorbar(im, orientation='horizontal')
>>> im = ax.imshow(img,
                   cmap='seismic')
```

Markers

```
>>> fig, ax = plt.subplots()
>>> ax.scatter(x,y,marker=".")
>>> ax.plot(x,y,marker="o")
```

Linestyles

```
>>> plt.plot(x,y,linewidth=4.0)
>>> plt.plot(x,y,ls='solid')
>>> plt.plot(x,y,ls='--')
>>> plt.plot(x,y,'--',x**2,y**2,'-.')
>>> plt.setp(lines,color='r',linewidth=4.0)
```

Text & Annotations

```
>>> ax.text(1,
            -2.1,
            'Example Graph',
            style='italic')
>>> ax.annotate("Sine",
                xy=(8, 0),
                xycoords='data',
                xytext=(10.5, 0),
                textcoords='data',
                arrowprops=dict(arrowstyle="->",
                connectionstyle="arc3"),)
```

Mathtext

```
>>> plt.title(r'$sigma_i=15$', fontsize=20)
```

Limits, Legends and Layouts

Limits & Autoscaling

```
>>> ax.margins(x=0.0,y=0.1) #Add padding to a plot
>>> ax.axis('equal') #Set the aspect ratio of the plot to 1
>>> ax.set(xlim=[0,10.5],ylim=[-1.5,1.5]) #Set limits for x-and y-axis
>>> ax.set_xlim(0,10.5) #Set limits for x-axis
```

Legends

```
>>> ax.set(title='An Example Axes', #Set a title and x-and y-axis labels
           ylabel='Y-Axis',
           xlabel='X-Axis')
>>> ax.legend(loc='best') #No overlapping plot elements
```

Ticks

```
>>> ax.xaxis.set(ticks=range(1,5), #Manually set x-ticks
                 ticklabels=[3,100,-12,"foo"])
>>> ax.tick_params(axis='y', #Make y-ticks longer and go in and out
                   direction='inout',
                   length=10)
```

Subplot Spacing

```
>>> fig3.subplots_adjust(wspace=0.5, #Adjust the spacing between subplots
                         hspace=0.3,
                         left=0.125,
                         right=0.9,
                         top=0.9,
                         bottom=0.1)
>>> fig.tight_layout() #Fit subplot(s) in to the figure area
```

Axis Spines

```
>>> ax1.spines['top'].set_visible(False)  #Make the top axis line for a plot invisible
>>> ax1.spines['bottom'].set_position(('outward',10)) #Move the bottom axis line outward
```

Python For Data Science
Seaborn Cheat Sheet

Learn Seaborn online at www.DataCamp.com

Statistical Data Visualization With Seaborn

The Python visualization library **Seaborn** is based on matplotlib and provides a high-level interface for drawing attractive statistical graphics.

Make use of the following aliases to import the libraries:

```
>>> import matplotlib.pyplot as plt
>>> import seaborn as sns
```

The basic steps to creating plots with Seaborn are:

1. Prepare some data
2. Control figure aesthetics
3. Plot with Seaborn
4. Further customize your plot
5. Show your plot

```
>>> import matplotlib.pyplot as plt
>>> import seaborn as sns
>>> tips = sns.load_dataset("tips") #Step 1
>>> sns.set_style("whitegrid") #Step 2
>>> g = sns.lmplot(x="tip", #Step 3
                   y="total_bill",
                   data=tips,
                   aspect=2)
>>> g = (g.set_axis_labels("Tip","Total bill(USD)").
set(xlim=(0,10),ylim=(0,100)))
>>> plt.title("title") #Step 4
>>> plt.show(g) #Step 5
```

1 Data

Also see Lists, NumPy & Pandas

```
>>> import pandas as pd
>>> import numpy as np
>>> uniform_data = np.random.rand(10, 12)
>>> data = pd.DataFrame({'x':np.arange(1,101),
                         'y':np.random.normal(0,4,100)})
```

Seaborn also offers built-in data sets:

```
>>> titanic = sns.load_dataset("titanic")
>>> iris = sns.load_dataset("iris")
```

2 Figure Aesthetics

Also see Matplotlib

```
>>> f, ax = plt.subplots(figsize=(5,6)) #Create a figure and one subplot
```

Seaborn styles

```
>>> sns.set() #(Re)set the seaborn default
>>> sns.set_style("whitegrid") #Set the matplotlib parameters
>>> sns.set_style("ticks", #Set the matplotlib parameters
                  {"xtick.major.size":8,
                   "ytick.major.size":8})
#Return a dict of params or use with with to temporarily set the style
>>> sns.axes_style("whitegrid")
```

Context Functions

```
>>> sns.set_context("talk") #Set context to "talk"
>>> sns.set_context("notebook", #Set context to "notebook",
                    font_scale=1.5, #Scale font elements and
                    rc={"lines.linewidth":2.5}) #override param mapping
```

Color Palette

```
>>> sns.set_palette("husl",3) #Define the color palette
>>> sns.color_palette("husl") #Use with with to temporarily set palette
>>> flatui = ["#9b59b6","#3498db","#95a5a6","#e74c3c","#34495e","#2ecc71"]
>>> sns.set_palette(flatui) #Set your own color palette
```

3 Plotting With Seaborn

Axis Grids

```
>>> g = sns.FacetGrid(titanic, #Subplot grid for plotting conditional relationships
                       col="survived",
                       row="sex")
>>> g = g.map(plt.hist,"age")
>>> sns.factorplot(x="pclass", #Draw a categorical plot onto a Facetgrid
                   y="survived",
                   hue="sex",
                   data=titanic)
>>> sns.lmplot(x="sepal_width", #Plot data and regression model fits across a FacetGrid
               y="sepal_length",
               hue="species",
               data=iris)
>>> h = sns.PairGrid(iris) #Subplot grid for plotting pairwise relationships
>>> h = h.map(plt.scatter)
>>> sns.pairplot(iris) #Plot pairwise bivariate distributions
>>> i = sns.JointGrid(x="x", #Grid for bivariate plot with marginal univariate plots
                      y="y",
                      data=data)
>>> i = i.plot(sns.regplot,
               sns.distplot)
>>> sns.jointplot("sepal_length", #Plot bivariate distribution
                  "sepal_width",
                  data=iris,
                  kind='kde')
```

4 Further Customizations

Also see Matplotlib

Axisgrid Objects

```
>>> g.despine(left=True) #Remove left spine
>>> g.set_ylabels("Survived") #Set the labels of the y-axis
>>> g.set_xticklabels(rotation=45) #Set the tick labels for x
>>> g.set_axis_labels("Survived", #Set the axis labels
                      "Sex")
>>> h.set(xlim=(0,5), #Set the limit and ticks of the x-and y-axis
          ylim=(0,5),
          xticks=[0,2.5,5],
          yticks=[0,2.5,5])
```

Plot

```
>>> plt.title("A Title") #Add plot title
>>> plt.ylabel("Survived") #Adjust the label of the y-axis
>>> plt.xlabel("Sex") #Adjust the label of the x-axis
>>> plt.ylim(0,100) #Adjust the limits of the y-axis
>>> plt.xlim(0,10) #Adjust the limits of the x-axis
>>> plt.setp(ax,yticks=[0,5]) #Adjust a plot property
>>> plt.tight_layout() #Adjust subplot params
```

Regression Plots

```
>>> sns.regplot(x="sepal_width", #Plot data and a linear regression model fit
                y="sepal_length",
                data=iris,
                ax=ax)
```

Distribution Plots

```
>>> plot = sns.distplot(data.y, #Plot univariate distribution
                        kde=False,
                        color="b")
```

Matrix Plots

```
>>> sns.heatmap(uniform_data,vmin=0,vmax=1) #Heatmap
```

Categorical Plots

Scatterplot

```
>>> sns.stripplot(x="species", #Scatterplot with one categorical variable
                  y="petal_length",
                  data=iris)
>>> sns.swarmplot(x="species", #Categorical scatterplot with non-overlapping points
                  y="petal_length",
                  data=iris)
```

Bar Chart

```
>>> sns.barplot(x="sex", #Show point estimates & confidence intervals with scatterplot glyphs
                y="survived",
                hue="class",
                data=titanic)
```

Count Plot

```
>>> sns.countplot(x="deck", #Show count of observations
                  data=titanic,
                  palette="Greens_d")
```

Point Plot

```
>>> sns.pointplot(x="class", #Show point estimates & confidence intervals as rectangular bars
                  y="survived",
                  hue="sex",
                  data=titanic,
                  palette={"male":"g",
                  "female":"m"},
                  markers=["^","o"],
                  linestyles=["-","--"])
```

Boxplot

```
>>> sns.boxplot(x="alive", #Boxplot
                y="age",
                hue="adult_male",
                data=titanic)
>>> sns.boxplot(data=iris,orient="h") #Boxplot with wide-form data
```

Violinplot

```
>>> sns.violinplot(x="age", #Violin plot
                   y="sex",
                   hue="survived",
                   data=titanic)
```

5 Show or Save Plot

Also see Matplotlib

```
>>> plt.show() #Show the plot
>>> plt.savefig("foo.png") #Save the plot as a figure
>>> plt.savefig("foo.png", #Save transparent figure
                transparent=True)
```

> Close & Clear

Also see Matplotlib

```
>>> plt.cla() #Clear an axis
>>> plt.clf() #Clear an entire figure
>>> plt.close() #Close a window
```

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Python For Data Science

PySpark RDD Cheat Sheet

Learn PySpark RDD online at www.DataCamp.com

Spark

PySpark is the Spark Python API that exposes the Spark programming model to Python.

> Initializing Spark

SparkContext

```
>>> from pyspark import SparkContext
>>> sc = SparkContext(master = 'local[2]')
```

Inspect SparkContext

```
>>> sc.version #Retrieve SparkContext version
>>> sc.pythonVer #Retrieve Python version
>>> sc.master #Master URL to connect to
>>> str(sc.sparkHome) #Path where Spark is installed on worker nodes
>>> str(sc.sparkUser()) #Retrieve name of the Spark User running SparkContext
>>> sc.appName #Return application name
>>> sc.applicationId #Retrieve application ID
>>> sc.defaultParallelism #Return default level of parallelism
>>> sc.defaultMinPartitions #Default minimum number of partitions for RDDs
```

Configuration

```
>>> from pyspark import SparkConf, SparkContext
>>> conf = (SparkConf()
            .setMaster("local")
            .setAppName("My app")
            .set("spark.executor.memory", "1g"))
>>> sc = SparkContext(conf = conf)
```

Using The Shell

In the PySpark shell, a special interpreter-aware SparkContext is already created in the variable called `sc`.

```
$ ./bin/spark-shell --master local[2]
$ ./bin/pyspark --master local[4] --py-files code.py
```

Set which master the context connects to with the `--master` argument, and add Python .zip, .egg or .py files to the runtime path by passing a comma-separated list to `--py-files`.

> Loading Data

Parallelized Collections

```
>>> rdd = sc.parallelize([('a',7),('a',2),('b',2)])
>>> rdd2 = sc.parallelize([('a',2),('d',1),('b',1)])
>>> rdd3 = sc.parallelize(range(100))
>>> rdd4 = sc.parallelize([("a",["x","y","z"]),
                           ("b",["p", "r"])])
```

External Data

Read either one text file from HDFS, a local file system or or any Hadoop-supported file system URI with `textFile()`, or read in a directory of text files with `wholeTextFiles()`

```
>>> textFile = sc.textFile("/my/directory/*.txt")
>>> textFile2 = sc.wholeTextFiles("/my/directory/")
```

> Retrieving RDD Information

Basic Information

```
>>> rdd.getNumPartitions() #List the number of partitions
>>> rdd.count() #Count RDD instances 3
>>> rdd.countByKey() #Count RDD instances by key
 defaultdict(<type 'int'>,{'a':2,'b':1})
>>> rdd.countByValue() #Count RDD instances by value
 defaultdict(<type 'int'>,{('b',2):1,('a',2):1,('a',7):1})
>>> rdd.collectAsMap() #Return (key,value) pairs as a dictionary
 {'a': 2,'b': 2}
>>> rdd3.sum() #Sum of RDD elements 4950
>>> sc.parallelize([]).isEmpty() #Check whether RDD is empty
 True
```

Summary

```
>>> rdd3.max() #Maximum value of RDD elements
 99
>>> rdd3.min() #Minimum value of RDD elements
 0
>>> rdd3.mean() #Mean value of RDD elements
 49.5
>>> rdd3.stdev() #Standard deviation of RDD elements
 28.866070047722118
>>> rdd3.variance() #Compute variance of RDD elements
 833.25
>>> rdd3.histogram(3) #Compute histogram by bins
 ([0,33,66,99],[33,33,34])
>>> rdd3.stats() #Summary statistics (count, mean, stdev, max & min)
```

> Applying Functions

```
#Apply a function to each RDD element
 >>> rdd.map(lambda x: x+(x[1],x[0])).collect()
  [('a',7,7,'a'),('a',2,2,'a'),('b',2,2,'b')]
#Apply a function to each RDD element and flatten the result
 >>> rdd5 = rdd.flatMap(lambda x: x+(x[1],x[0]))
 >>> rdd5.collect()
  ['a',7,7,'a','a',2,2,'a','b',2,2,'b']
#Apply a flatMap function to each (key,value) pair of rdd4 without changing the keys
>>> rdd4.flatMapValues(lambda x: x).collect()
 [('a','x'),('a','y'),('a','z'),('b','p'),('b','r')]
```

> Selecting Data

Getting

```
>>> rdd.collect() #Return a list with all RDD elements
 [('a', 7), ('a', 2), ('b', 2)]
>>> rdd.take(2) #Take first 2 RDD elements
 [('a', 7), ('a', 2)]
>>> rdd.first() #Take first RDD element
 ('a', 7)
>>> rdd.top(2) #Take top 2 RDD elements
 [('b', 2), ('a', 7)]
```

Sampling

```
>>> rdd3.sample(False, 0.15, 81).collect() #Return sampled subset of rdd3
 [3,4,27,31,40,41,42,43,60,76,79,80,86,97]
```

Filtering

```
>>> rdd.filter(lambda x: "a" in x).collect()  #Filter the RDD
 [('a',7),('a',2)]
>>> rdd5.distinct().collect() #Return distinct RDD values
 ['a',2,'b',7]
>>> rdd.keys().collect() #Return (key,value) RDD's keys
 ['a', 'a', 'b']
```

> Iterating

```
>>> def g(x): print(x)
>>> rdd.foreach(g) #Apply a function to all RDD elements
 ('a', 7)
 ('b', 2)
 ('a', 2)
```

> Reshaping Data

Reducing

```
>>> rdd.reduceByKey(lambda x,y : x+y).collect() #Merge the rdd values for each key
 [('a',9),('b',2)]
>>> rdd.reduce(lambda a, b: a + b) #Merge the rdd values
 ('a',7,'a',2,'b',2)
```

Grouping by

```
>>> rdd3.groupBy(lambda x: x % 2) #Return RDD of grouped values
        .mapValues(list)
        .collect()
>>> rdd.groupByKey() #Group rdd by key
       .mapValues(list)
       .collect()
 [('a',[7,2]),('b',[2])]
```

Aggregating

```
>>> seqOp = (lambda x,y: (x[0]+y,x[1]+1))
>>> combOp = (lambda x,y:(x[0]+y[0],x[1]+y[1]))
#Aggregate RDD elements of each partition and then the results
>>> rdd3.aggregate((0,0),seqOp,combOp)
 (4950,100)
 #Aggregate values of each RDD key
>>> rdd.aggregateByKey((0,0),seqop,combop).collect()
 [('a',(9,2)), ('b',(2,1))]
#Aggregate the elements of each partition, and then the results
>>> rdd3.fold(0,add)
 4950
#Merge the values for each key
>>> rdd.foldByKey(0, add).collect()
 [('a',9),('b',2)]
#Create tuples of RDD elements by applying a function
>>> rdd3.keyBy(lambda x: x+x).collect()
```

> Mathematical Operations

```
>>> rdd.subtract(rdd2).collect() #Return each rdd value not contained in rdd2
 [('b',2),('a',7)]
#Return each (key,value) pair of rdd2  with no matching key in rdd
>>> rdd2.subtractByKey(rdd).collect()
 [('d', 1)]
>>> rdd.cartesian(rdd2).collect() #Return the Cartesian product of rdd and rdd2
```

> Sort

```
>>> rdd2.sortBy(lambda x: x[1]).collect() #Sort RDD by given function
 [('d',1),('b',1),('a',2)]
>>> rdd2.sortByKey().collect() #Sort (key, value) RDD by key
 [('a',2),('b',1),('d',1)]
```

> Repartitioning

```
>>> rdd.repartition(4) #New RDD with 4 partitions
>>> rdd.coalesce(1) #Decrease the number of partitions in the RDD to 1
```

> Saving

```
>>> rdd.saveAsTextFile("rdd.txt")
>>> rdd.saveAsHadoopFile("hdfs://namenodehost/parent/child",
                         'org.apache.hadoop.mapred.TextOutputFormat')
```

> Stopping SparkContext

```
>>> sc.stop()
```

> Execution

```
$ ./bin/spark-submit examples/src/main/python/pi.py
```

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Python For Data Science

PySpark SQL Basics Cheat Sheet

Learn PySpark SQL online at www.DataCamp.com

PySpark & Spark SQL

Spark SQL is Apache Spark's module for working with structured data.

> Initializing SparkSession

A SparkSession can be used create DataFrame, register DataFrame as tables, execute SQL over tables, cache tables, and read parquet files.

```
>>> from pyspark.sql import SparkSession
>>> spark = SparkSession \
        .builder \
        .appName("Python Spark SQL basic example") \
        .config("spark.some.config.option", "some-value") \
        .getOrCreate()
```

> Creating DataFrames

From RDDs

```
>>> from pyspark.sql.types import *
```

Infer Schema

```
>>> sc = spark.sparkContext
>>> lines = sc.textFile("people.txt")
>>> parts = lines.map(lambda l: l.split(","))
>>> people = parts.map(lambda p: Row(name=p[0],age=int(p[1])))
>>> peopledf = spark.createDataFrame(people)
```

Specify Schema

```
>>> people = parts.map(lambda p: Row(name=p[0],
                                     age=int(p[1].strip())))
>>> schemaString = "name age"
>>> fields = [StructField(field_name, StringType(), True) for
field_name in schemaString.split()]
>>> schema = StructType(fields)
>>> spark.createDataFrame(people, schema).show()
```

```
+--------+---+
|    name|age|
+--------+---+
|    Mine| 28|
|   Filip| 29|
|Jonathan| 30|
+--------+---+
```

From Spark Data Sources

JSON

```
>>> df = spark.read.json("customer.json")
>>> df.show()
```

```
+--------------------+---+---------+--------+--------------------+
|             address|age|firstName |lastName|         phoneNumber|
+--------------------+---+---------+--------+--------------------+
|[New York,10021,N...| 25|     John|   Smith|[[212 555-1234,ho...|
|[New York,10021,N...| 21|     Jane|     Doe|[[322 888-1234,ho...|
+--------------------+---+---------+--------+--------------------+
```

```
>>> df2 = spark.read.load("people.json", format="json")
```

Parquet files

```
>>> df3 = spark.read.load("users.parquet")
```

TXT files

```
>>> df4 = spark.read.text("people.txt")
```

> Filter

```
#Filter entries of age, only keep those records of which the values are >24
>>> df.filter(df["age"]>24).show()
```

> Duplicate Values

```
>>> df = df.dropDuplicates()
```

> Queries

```
>>> from pyspark.sql import functions as F
```

Select

```
>>> df.select("firstName").show() #Show all entries in firstName column
>>> df.select("firstName","lastName") \
      .show()
>>> df.select("firstName", #Show all entries in firstName, age and type
              "age",
              explode("phoneNumber") \
              .alias("contactInfo")) \
      .select("contactInfo.type",
              "firstName",
              "age") \
      .show()
>>> df.select(df["firstName"],df["age"]+ 1)  #Show all entries in firstName and age,
      .show()                                  add 1 to the entries of age
>>> df.select(df['age'] > 24).show() #Show all entries where age >24
```

When

```
>>> df.select("firstName", #Show firstName and 0 or 1 depending on age >30
              F.when(df.age > 30, 1) \
              .otherwise(0)) \
      .show()
>>> df[df.firstName.isin("Jane","Boris")] #Show firstName if in the given options
                 .collect()
```

Like

```
>>> df.select("firstName", #Show firstName, and lastName is TRUE if lastName is like Smith
              df.lastName.like("Smith")) \
      .show()
```

Startswith - Endswith

```
>>> df.select("firstName", #Show firstName, and TRUE if lastName starts with Sm
              df.lastName \
                .startswith("Sm")) \
      .show()
>>> df.select(df.lastName.endswith("th"))\ #Show last names ending in th
      .show()
```

Substring

```
>>> df.select(df.firstName.substr(1, 3) \ #Return substrings of firstName
                          .alias("name")) \
      .collect()
```

Between

```
>>> df.select(df.age.between(22, 24)) \ #Show age: values are TRUE if between 22 and 24
      .show()
```

> Add, Update & Remove Columns

Adding Columns

```
>>> df = df.withColumn('city',df.address.city) \
           .withColumn('postalCode',df.address.postalCode) \
           .withColumn('state',df.address.state) \
           .withColumn('streetAddress',df.address.streetAddress) \
           .withColumn('telePhoneNumber', explode(df.phoneNumber.number)) \
           .withColumn('telePhoneType', explode(df.phoneNumber.type))
```

Updating Columns

```
>>> df = df.withColumnRenamed('telePhoneNumber', 'phoneNumber')
```

Removing Columns

```
>>> df = df.drop("address", "phoneNumber")
>>> df = df.drop(df.address).drop(df.phoneNumber)
```

> Missing & Replacing Values

```
>>> df.na.fill(50).show() #Replace null values
>>> df.na.drop().show() #Return new df omitting rows with null values
>>> df.na \ #Return new df replacing one value with another
      .replace(10, 20) \
      .show()
```

> GroupBy

```
>>> df.groupBy("age")\ #Group by age, count the members in the groups
      .count() \
      .show()
```

> Sort

```
>>> peopledf.sort(peopledf.age.desc()).collect()
>>> df.sort("age", ascending=False).collect()
>>> df.orderBy(["age","city"],ascending=[0,1])\
      .collect()
```

> Repartitioning

```
>>> df.repartition(10)\ #df with 10 partitions
      .rdd \
      .getNumPartitions()
>>> df.coalesce(1).rdd.getNumPartitions() #df with 1 partition
```

> Running Queries Programmatically

Registering DataFrames as Views

```
>>> peopledf.createGlobalTempView("people")
>>> df.createTempView("customer")
>>> df.createOrReplaceTempView("customer")
```

Query Views

```
>>> df5 = spark.sql("SELECT * FROM customer").show()
>>> peopledf2 = spark.sql("SELECT * FROM global_temp.people")\
                 .show()
```

> Inspect Data

```
>>> df.dtypes #Return df column names and data types
>>> df.show() #Display the content of df
>>> df.head() #Return first n rows
>>> df.first() #Return first row
>>> df.take(2) #Return the first n rows >>> df.schema Return the schema of df
>>> df.describe().show() #Compute summary statistics >>> df.columns Return the columns of df
>>> df.count() #Count the number of rows in df
>>> df.distinct().count() #Count the number of distinct rows in df
>>> df.printSchema() #Print the schema of df
>>> df.explain() #Print the (logical and physical) plans
```

> Output

Data Structures

```
>>> rdd1 = df.rdd #Convert df into an RDD
>>> df.toJSON().first() #Convert df into a RDD of string
>>> df.toPandas() #Return the contents of df as Pandas DataFrame
```

Write & Save to Files

```
>>> df.select("firstName", "city")\
      .write \
      .save("nameAndCity.parquet")
>>> df.select("firstName", "age") \
      .write \
      .save("namesAndAges.json",format="json")
```

> Stopping SparkSession

```
>>> spark.stop()
```

Top Machine Learning Algorithms

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ALGORITHM	DESCRIPTION	APPLICATIONS	ADVANTAGES	DISADVANTAGES
Supervised Learning				
Linear Models — **Linear Regression**	A simple algorithm that models a linear relationship between inputs and a continuous numerical output variable	USE CASES 1. Stock price prediction 2. Predicting housing prices 3. Predicting customer lifetime value	1. Explainable method 2. Interpretable results by its output coefficients 3. Faster to train than other machine learning models	1. Assumes linearity between inputs and output 2. Sensitive to outliers 3. Can underfit with small, high-dimensional data
Linear Models — **Logistic Regression**	A simple algorithm that models a linear relationship between inputs and a categorical output (1 or 0)	USE CASES 1. Credit risk score prediction 2. Customer churn prediction	1. Interpretable and explainable 2. Less prone to overfitting when using regularization 3. Applicable for multi-class predictions	1. Assumes linearity between inputs and outputs 2. Can overfit with small, high-dimensional data
Linear Models — **Ridge Regression**	Part of the regression family — it penalizes features that have low predictive outcomes by shrinking their coefficients closer to zero. Can be used for classification or regression	USE CASES 1. Predictive maintenance for automobiles 2. Sales revenue prediction	1. Less prone to overfitting 2. Best suited where data suffer from multicollinearity 3. Explainable & interpretable	1. All the predictors are kept in the final model 2. Doesn't perform feature selection
Linear Models — **Lasso Regression**	Part of the regression family — it penalizes features that have low predictive outcomes by shrinking their coefficients to zero. Can be used for classification or regression	USE CASES 1. Predicting housing prices 2. Predicting clinical outcomes based on health data	1. Less prone to overfitting 2. Can handle high-dimensional data 3. No need for feature selection	1. Can lead to poor interpretability as it can keep highly correlated variables
Tree-Based Models — **Decision Tree**	Decision Tree models make decision rules on the features to produce predictions. It can be used for classification or regression	USE CASES 1. Customer churn prediction 2. Credit score modeling 3. Disease prediction	1. Explainable and interpretable 2. Can handle missing values	1. Prone to overfitting 2. Sensitive to outliers
Tree-Based Models — **Random Forests**	An ensemble learning method that combines the output of multiple decision trees	USE CASES 1. Credit score modeling 2. Predicting housing prices	1. Reduces overfitting 2. Higher accuracy compared to other models	1. Training complexity can be high 2. Not very interpretable
Tree-Based Models — **Gradient Boosting Regression**	Gradient Boosting Regression employs boosting to make predictive models from an ensemble of weak predictive learners	USE CASES 1. Predicting car emissions 2. Predicting ride hailing fare amount	1. Better accuracy compared to other regression models 2. It can handle multicollinearity 3. It can handle non-linear relationships	1. Sensitive to outliers and can therefore cause overfitting 2. Computationally expensive and has high complexity
Tree-Based Models — **XGBoost**	Gradient Boosting algorithm that is efficient & flexible. Can be used for both classification and regression tasks	USE CASES 1. Churn prediction 2. Claims processing in insurance	1. Provides accurate results 2. Captures non linear relationships	1. Hyperparameter tuning can be complex 2. Does not perform well on sparse datasets
Tree-Based Models — **LightGBM Regressor**	A gradient boosting framework that is designed to be more efficient than other implementations	USE CASES 1. Predicting flight time for airlines 2. Predicting cholesterol levels based on health data	1. Can handle large amounts of data 2. Computational efficient & fast training speed 3. Low memory usage	1. Can overfit due to leaf-wise splitting and high sensitivity 2. Hyperparameter tuning can be complex
Unsupervised Learning				
Clustering — **K-Means**	K-Means is the most widely used clustering approach—it determines K clusters based on euclidean distances	USE CASES 1. Customer segmentation 2. Recommendation systems	1. Scales to large datasets 2. Simple to implement and interpret 3. Results in tight clusters	1. Requires the expected number of clusters from the beginning 2. Has troubles with varying cluster sizes and densities
Clustering — **Hierarchical Clustering**	A "bottom-up" approach where each data point is treated as its own cluster—and then the closest two clusters are merged together iteratively	USE CASES 1. Fraud detection 2. Document clustering based on similarity	1. There is no need to specify the number of clusters 2. The resulting dendrogram is informative	1. Doesn't always result in the best clustering 2. Not suitable for large datasets due to high complexity
Clustering — **Gaussian Mixture Models**	A probabilistic model for modeling normally distributed clusters within a dataset	USE CASES 1. Customer segmentation 2. Recommendation systems	1. Computes a probability for an observation belonging to a cluster 2. Can identify overlapping clusters 3. More accurate results compared to K-means	1. Requires complex tuning 2. Requires setting the number of expected mixture components or clusters
Association — **Apriori algorithm**	Rule based approach that identifies the most frequent itemset in a given dataset where prior knowledge of frequent itemset properties is used	USE CASES 1. Product placements 2. Recommendation engines 3. Promotion optimization	1. Results are intuitive and Interpretable 2. Exhaustive approach as it finds all rules based on the confidence and support	1. Generates many uninteresting itemsets 2. Computationally and memory intensive. 3. Results in many overlapping item sets

Python For Data Science
Keras Cheat Sheet

Learn Keras online at www.DataCamp.com

Keras

Keras is a powerful and easy-to-use deep learning library forTheano and TensorFlow that provides a high-level neural networks API to develop and evaluate deep learning models.

A Basic Example

```
>>> import numpy as np
>>> from tensorflow.keras.models import Sequential
>>> from tensorflow.keras.layers import Dense
>>> data = np.random.random((1000,100))
>>> labels = np.random.randint(2,size=(1000,1))
>>> model = Sequential()
>>> model.add(Dense(32,
                    activation='relu',
                    input_dim=100))
>>> model.add(Dense(1, activation='sigmoid'))
>>> model.compile(optimizer='rmsprop',
                  loss='binary_crossentropy',
                  metrics=['accuracy'])
>>> model.fit(data,labels,epochs=10,batch_size=32)
>>> predictions = model.predict(data)
```

> Data

Your data needs to be stored as NumPy arrays or as a list of NumPy arrays. Ideally, you split the data in training and test sets, for which you can also resort to the `train_test_split` module of `sklearn.cross_validation`.

Keras Data Sets

```
>>> from tensorflow.keras.datasets import boston_housing, mnist, cifar10, imdb
>>> (x_train,y_train),(x_test,y_test) = mnist.load_data()
>>> (x_train2,y_train2),(x_test2,y_test2) = boston_housing.load_data()
>>> (x_train3,y_train3),(x_test3,y_test3) = cifar10.load_data()
>>> (x_train4,y_train4),(x_test4,y_test4) = imdb.load_data(num_words=20000)
>>> num_classes = 10
```

Other

```
>>> from urllib.request import urlopen
>>> data =
np.loadtxt(urlopen("http://archive.ics.uci.edu/ml/machine-learning-databases/pima-indians-diabetes/pima-indians-diabetes.data"),delimiter=",")
>>> X = data[:,0:8]
>>> y = data [:,8]
```

> Preprocessing

Also see NumPy & Scikit-Learn

Sequence Padding

```
>>> from tensorflow.keras.preprocessing import sequence
>>> x_train4 = sequence.pad_sequences(x_train4,maxlen=80)
>>> x_test4 = sequence.pad_sequences(x_test4,maxlen=80)
```

One-Hot Encoding

```
>>> from tensorflow.keras.utils import to_categorical
>>> Y_train = to_categorical(y_train, num_classes)
>>> Y_test = to_categorical(y_test, num_classes)
>>> Y_train3 = to_categorical(y_train3, num_classes)
>>> Y_test3 = to_categorical(y_test3, num_classes)
```

> Model Architecture

Sequential Model

```
>>> from tensorflow.keras.models import Sequential
>>> model = Sequential()
>>> model2 = Sequential()
>>> model3 = Sequential()
```

Multilayer Perceptron (MLP)

Binary Classification

```
>>> from tensorflow.keras.layers import Dense
>>> model.add(Dense(12,
                    input_dim=8,
                    kernel_initializer='uniform',
                    activation='relu'))
>>> model.add(Dense(8,kernel_initializer='uniform',activation='relu'))
>>> model.add(Dense(1,kernel_initializer='uniform',activation='sigmoid'))
```

Multi-Class Classification

```
>>> from tensorflow.keras.layers import Dropout
>>> model.add(Dense(512,activation='relu',input_shape=(784,)))
>>> model.add(Dropout(0.2))
>>> model.add(Dense(512,activation='relu'))
>>> model.add(Dropout(0.2))
>>> model.add(Dense(10,activation='softmax'))
```

Regression

```
>>> model.add(Dense(64,activation='relu',input_dim=train_data.shape[1]))
>>> model.add(Dense(1))
```

Convolutional Neural Network (CNN)

```
>>> from tensorflow.keras.layers import Activation,Conv2D,MaxPooling2D,Flatten
>>> model2.add(Conv2D(32,(3,3),padding='same',input_shape=x_train.shape[1:]))
>>> model2.add(Activation('relu'))
>>> model2.add(Conv2D(32,(3,3)))
>>> model2.add(Activation('relu'))
>>> model2.add(MaxPooling2D(pool_size=(2,2)))
>>> model2.add(Dropout(0.25))
>>> model2.add(Flatten())
>>> model2.add(Dense(512))
>>> model2.add(Activation('relu'))
>>> model2.add(Dropout(0.5))
>>> model2.add(Dense(num_classes))
>>> model2.add(Activation('softmax'))
```

Recurrent Neural Network (RNN)

```
>>> from tensorflow.keras.klayers import Embedding,LSTM
>>> model3.add(Embedding(20000,128))
>>> model3.add(LSTM(128,dropout=0.2,recurrent_dropout=0.2))
>>> model3.add(Dense(1,activation='sigmoid'))
```

> Prediction

```
>>> model3.predict(x_test4, batch_size=32)
>>> model3.predict_classes(x_test4,batch_size=32)
```

Train and Test Sets

```
>>> from sklearn.model_selection import train_test_split
>>> X_train5,X_test5,y_train5,y_test5 = train_test_split(X, y,
                                                         test_size=0.33,
                                                         random_state=42)
```

Standardization/Normalization

```
>>> from sklearn.preprocessing import StandardScaler
>>> scaler = StandardScaler().fit(x_train2)
>>> standardized_X = scaler.transform(x_train2)
>>> standardized_X_test = scaler.transform(x_test2)
```

> Inspect Model

```
>>> model.output_shape #Model output shape
>>> model.summary() #Model summary representation
>>> model.get_config() #Model configuration
>>> model.get_weights() #List all weight tensors in the model
```

> Compile Model

MLP: Binary Classification

```
>>> model.compile(optimizer='adam',
                  loss='binary_crossentropy',
                  metrics=['accuracy'])
```

MLP: Multi-Class Classification

```
>>> model.compile(optimizer='rmsprop',
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
```

MLP: Regression

```
>>> model.compile(optimizer='rmsprop',
                  loss='mse',
                  metrics=['mae'])
```

Recurrent Neural Network

```
>>> model3.compile(loss='binary_crossentropy',
                   optimizer='adam',
                   metrics=['accuracy'])
```

> Model Training

```
>>> model3.fit(x_train4,
               y_train4,
               batch_size=32,
               epochs=15,
               verbose=1,
               validation_data=(x_test4,y_test4))
```

> Evaluate Your Model's Performance

```
>>> score = model3.evaluate(x_test,
                            y_test,
                            batch_size=32)
```

> Save/ Reload Models

```
>>> from keras.models import load_model
>>> model3.save('model_file.h5')
>>> my_model = load_model('my_model.h5')
```

> Model Fine-tuning

Optimization Parameters

```
>>> from tensorflow.keras.optimizers import RMSprop
>>> opt = RMSprop(lr=0.0001, decay=1e-6)
>>> model2.compile(loss='categorical_crossentropy',
                   optimizer=opt,
                   metrics=['accuracy'])
```

Early Stopping

```
>>> from tensorflow.keras.callbacks import EarlyStopping
>>> early_stopping_monitor = EarlyStopping(patience=2)
>>> model3.fit(x_train4,
               y_train4,
               batch_size=32,
               epochs=15,
               validation_data=(x_test4,y_test4),
               callbacks=[early_stopping_monitor])
```